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Abstract

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Keywords

learning, cloud, mobile, facilitating, collaborative, enhancing, taas, teamwork, system, performance

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Facilitating Collaborative Learning in TaaS: a Mobile Cloud System for Enhancing Teamwork Performance

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Abstract—Mobile cloud-based learning is a novel trend that brings many advantages to distributed learners to achieve collaborative learning, but it still lacks of mechanisms to enhance their teamwork performances. To make up that shortcoming, combining the features of cloud environment, we have identified a learning flow, a specification of workflow, based on Kolb team learning experience. This novel learning flow can be executed by our newly designed system, Teamwork as a Service (TaaS), in conjunction with cloud-hosting learning management system, following which learners benefit from functions given by cloud-based services, separately for organizing cloud jigsaw classroom, planning and publishing tasks, rational task allocation and mutual supervision. We introduce a genetic algorithm method for grouping learners into appropriate teams, for two different scenarios of expectations for forming teams. Experimental results prove that our approach is workable to facilitate teamwork, while learners' capabilities and preferences are being taken into consideration.

Keywords—mobile learning, cloud computing, enhancing teamwork performance, genetic algorithm.

I. INTRODUCTION

Nowadays, the ways for learners to achieve educational services and resources are no longer limited in the traditional classroom, as the distance education is booming with the assistance of electronic equipment and network. In other words, the electronic learning (e-learning) is gaining wide acceptance. A newly emerged form of e-learning is mobile learning (m-learning), which allows learners to participate in learning scenes formally utilizing mobile devices regardless of their locations [1].

Education providers are interested in delivering the education service by using the learning management system (LMS) to assemble all needed materials, enabling easy access and user-friendly interface [2]. Because most of LMSs are web-based and supported by the widespread use of wireless network, directly accessing LMSs from mobile devices becomes a common style of m-learning.

M-learning thrives recently with the import of a new trend that it is embraced with a novel technology, cloud computing. The fundamental of cloud computing is that computing is arranged in large distributed systems instead of in local computers or remote servers [3]. Benefiting from those, the

user terminal is free to access massive resources and computing capabilities from the cloud on demand, which would ultimately suffice as an input and output device [4].

To realize that evolvement of m-learning, migrating existing LMSs to cloud or developing the upgrade versions of original ones over cloud platform are feasible solutions, from which a novel way of m-learning, namely mobile cloud-based learning, comes out. Functions for supporting collaborative learning are gradually consummated in several popular cloud-hosting LMSs [5]. It can be found the collaborative learning has a favorable environment to happen more and more frequently among learners who have similar learning purposes. Accordingly, to make full use of mobile cloud-based learning, collaborative learning is not only adopted as a significant approach by teachers in school education, but also helpful in business area in which companies draw its aid to train employees or arrange them into teamwork if a task needs multiple persons working towards a common goal.

The physical condition of organizing collaborative learning is relatively completed. However, to our knowledge, there are comparatively less researches aim to facilitate the collaborative learning in such new environment as well as enhance learners' teamwork performance. In this paper, we introduce a novel approach to fill those gaps, by offering a service-oriented system, 'Teamwork as a Service' (TaaS), which works as a third-party system by adding teamwork-focused functions to current cloud-hosting LMSs.

II. MOTIVATION

The context of mobile cloud-based learning is more specific than traditional learning, where learners are distributed over large geographical areas. The learners who participate in virtual teams are more focused on task-related outcomes and time constraints [6], and lack guidance to introduce them into effective direction of learning path. Thus, once a teamwork assignment is given in an m-learning course, because of geographical separation and even time differences, learners are faced with many unpredictable difficulties for which they are not prepared enough and perhaps the biggest of these is insufficient communication [7] [8][9].

In addition to this, there are problems which also occur in traditional team learning which can negatively affect mobile

team learning. The literature shows that learners belonging to the same team often have differing learning styles and therefore require diverse learning approaches [10]. Each learner's expectations and preferences also influence their motivation to work to the limit of their abilities [11]. Current assessment criteria also lack the mechanism to track the entire learning experience, and are generally based on learners' final outcomes. This means that problems can be hard to diagnose and solve in a timely manner, while the team learning is actually in progress.

III. SERVICE DESIGN AND WORK PATTERNS

Combining the feature of the cloud, over which systems are normally service-oriented, practitioners and developers are free to choose useful services on demand and composite them together to establish a virtual environment that provides more comprehensive functions than output by the operation of just one application or system [12]. We draw the idea of Kolb learning experience (KTLE) to orchestrate a learning flow [13], a specification of workflow, to make up such issues in order to facilitate collaborative learning [14]. As KTLE has seven modules, each of the five services of TaaS takes one or more of them to refine a certain type of learning activity. These learning activities are structured into the learning flow, by executing TaaS service by service in conjunction with the cloud-hosting LMSs, shown as Figure 1. As their partner, consequently TaaS is service-oriented to guarantee the flexible interaction with those systems, and better to be hosted over cloud to borrow the massive computing power of the cloud. Specifically, leveraging the cloud can enable the multiple accesses from education providers in different level by one large-scale deployment, and let TaaS be protected by load balancers in the cloud to keep the robustness when suddenly increasing visit volumes occur.

As TaaS emphasizes to build a better context for collaborative learning to enhance learners' teamwork performance, it consists of five web services. The Survey Service offers the workaround for covering the unstable communication condition of mobile environment in order to ensure learners are able to know about one another; the Jigsaw Service organizes efficient discussions among learners; the Bulletin Service allows learners to clearly plan for their team

assignments; the Monitor service provides mutual supervision among learners while the teamwork is in progress. Moreover, because rational grouping is an important premise for each team of learners to perform better [15] [16], the Inference Service allocates each learner to a specific subtask in regard of their learning styles and preferences, while the learners working towards the common task therefore form as an aggressive team.

A. The Survey Service

For "introduction to teams", we designed a Survey Service which offers interfaces to learners for answering questions in order to investigate their capabilities. Considering the limitation of screen sizes and typing method of the mobile devices, the survey is in single-answer multiple-choice format. The survey can be operated as self-assessment or peer-assessment, which means the respondents can evaluate either themselves or the other group members working with them

There are five sets of questions which are pre-installed in the Survey Service, four of which are for the four aspects (accommodating, assimilating, converging, diverging) of Kolb's learning style (KLS) [17][18], and the last is for comprehensive teamwork skills. These questionnaires come from [19] [20], and can be extended or reduced by teachers manually. For the k^{th} learner L^k , each separated set of questionnaire results about him/her are compiled and calculated. Then we got five values: AC^k , AS^k , C^k , D^k and CT^k . They represent the capability values of accommodating, assimilating, converging, diverging and comprehensive teamwork skills, respectively. Therein, we let a 4-tuple $KLS^k = \{AC^k, AS^k, C^k, D^k\}$ denote the KLS capability values of L^k . Note each value is a real between 1 and 10.

B. The Jigsaw Service

The Jigsaw method introduced in [21] is classic for deepening learners' understanding of "team purpose", the three stages of which can be imitated by the Jigsaw Service:

For "initial discussion in original team", the Jigsaw Service groups learners into four-person original teams, keeping the total comprehensive teamwork skills of each equal with the

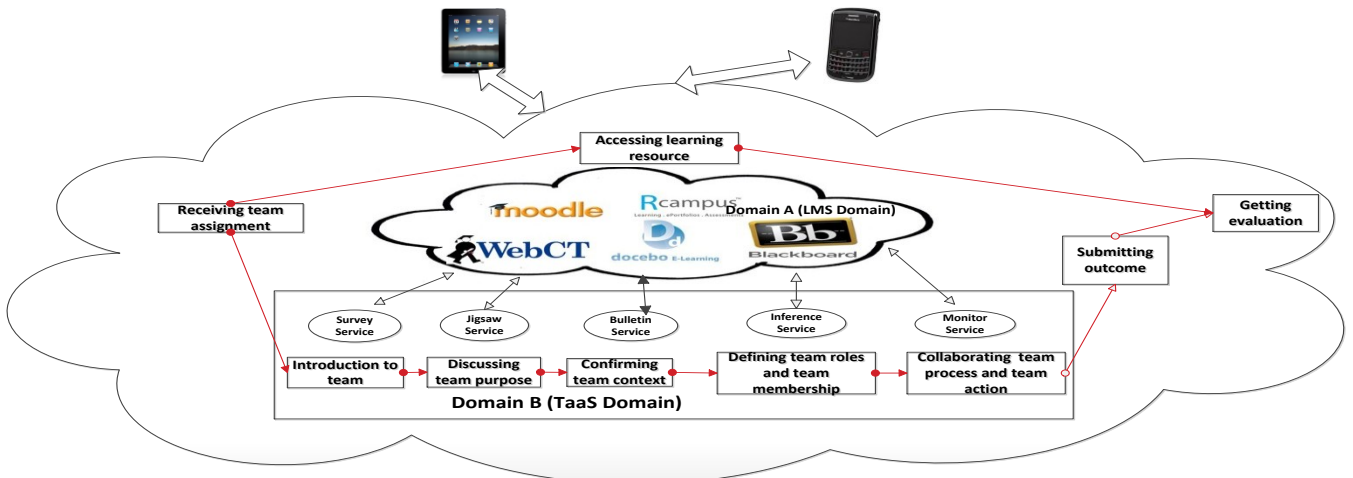


Figure 1. Teamwork-Enhanced Learning Flow for Mobile Cloud-based Learning

others'. In each original team, the four KLS team roles are separately assigned to members [22].

For “joining expert team to refine cognition”, it rebuilds four expert teams, within each of which learners who played the same roles in the original teams are involved.

For “backing to original group to teach others what was gained in expert group”, it redirects learners into the original teams from which they have come.

C. The Bulletin Service

The Bulletin Service provides a platform for learners to collaboratively define the “team context” and on which they are able to publish schedules of alternative tasks, each of which is suitable for an imaginary team and consists of several subtasks. The publisher of a task is required to mark the difficulty of its subtasks as expected-achievable values in KLS, while other learners are free to show their preferences regarding those when browsing. As it is in WYSIWYG mode, publishing the task schedule through user interface is easily done. In addition, subtasks' difficulty and learners' preferences are also marked using a multiple-choice format.

The number of subtasks of each task can be pre-set by teachers. Taking example by the real team learning condition, we suppose the numbers is between 3 and 6 and learners are required to meet this task size while they are pre-planning.

For a published S^{ij} , which is the j^{th} subtask of the i^{th} task, its difficulty in KLS is represented by expected-achievable values, in order to mark it to be better completed by a learner who has the appropriate capabilities. The values are set in a 4-tuple ST^{ij} , where $ST^{ij} = \{AC^{ij}, AS^{ij}, C^{ij}, D^{ij}\}$, each value is a real between 1 and 10.

For L^k 's preference to the S^{ij} , we represent it by a variable P_k^{ij} . The P_k^{ij} is an integer between 1 and 5, the higher the grade is, the more preferred by the learner to do a subtask.

D. The Inference Service

For “team membership” and “team roles”, the Inference Service is the core of our solution as it attempts to solve the problem caused by the specialization of mobile cloud based learning, using reasoning mechanisms.

Referring the capabilities and the preferences of learners, and the expected-achievable values of subtasks, the operation principle of this service is matching each learner to the most appropriate subtask. On the other hand, in the inference process, learners who take subtasks belonging to the same task will be grouped into the same team, so that the attributes of whole strengths of a team is taken into consideration, accordingly, a successful team is probably not the set of the best learners.

We suppose two ways of forming a team, with different focus. They are:

“Keeping the balance between each team”, which means the upcoming teams will have approximate comprehensive teamwork skills. In addition, the learners' preferences and capability levels are diverse in confined shapes, meaning that if we regard each team as an independent unit, its integrated

preferences and capability values are highly close to those of other units. Therefore, we can say that the inter-team competition between the upcoming teams starts from the same scratch line and is assured fair.

“Letting the learners show their capabilities mostly”, which means each of them is able to put their superiorities to use as much as possible, so that whether the team members are “good at” and “happy to” their upcoming subtasks will be the main indexes that direct the reasoning processing of task allocation.

The detailed computing process of the GA will be discussed in Section IV.

E. The Monitor Service

The Monitor Service aims to provide mutual supervision for “team process” and “team action”. In each team, each learner is assigned as the coordinator for another. The pair of completer/coordinator is linked by a file transmission channel, through which the completer sends his periodical outcome to the coordinator, who takes responsibility for judging whether he has reached an acceptable rate of progress and is capable of continuing or not, by grading him “satisfactory” or “unsatisfactory”. A penalty mechanism is embedded in this service, which automatically deducts the completer's marks if he gets any “unsatisfactory” grade on a stage of his work in progress.

IV. GENETIC ALGORITHM FOR TEAMWORK-ENHANCED TASK ALLOCATION

In this section, we introduce the computing process of GA, which is for the teamwork-enhanced task allocation executed by the Inference Service.

1) Problem Modeling

For initialization, the Inference Service checks whether a learner L^k is appropriate to accomplish a S^{ij} by calculating. We introduce two variables to describe the deviation of learner versus subtask. The first variable DeP denotes the preference gap between learner's ideal and reality, where:

$$DeP_k^{ij} = 5 - P_k^{ij} \quad (1)$$

And the second variable DeK denotes deviation of learner's KLS capability values versus a subtask's expected-achievable values, where:

$$DeK_k^{ij} = -\{sign[\sum (KLS^k - ST^{ij})]\} \cdot \|KLS^k - ST^{ij}\| \quad (2)$$

Subject to:

$$KLS^k - ST^{ij} = \{AC^k - AC^{ij}, AS^k - AS^{ij}, C^k - C^{ij}, D^k - D^{ij}\} \quad (3)$$

$$\|KLS^k - ST^{ij}\| = \sqrt{(AC^k - AC^{ij})^2 + (AS^k - AS^{ij})^2 + (C^k - C^{ij})^2 + (D^k - D^{ij})^2} \quad (4)$$

Both of these deviations are the lower the better. An ideal DeK_k^{ij} is below 0.

If a potential team x is allocated with the $task^i$, we use ${}^xDeP^i$, ${}^xDeK^i$, ${}^xCT^i$ to represent its sum of DeP , DeK , CT , respectively.

2) Genetic Algorithm Method

GA is an optimal self-adaptive heuristic algorithm, which simulates the natural biological selection and genetic evolution mechanism. The basic idea of GA is inspired by evolution

process in the natural world, to optimize candidate solutions towards better ones [23] [24]. Traditionally, candidate solutions start randomly and change in generations, by selection, crossover and mutation. Every generation is evaluated by a fitness function and the new generation is then used in the next iteration of the algorithm. Once a satisfactory of fitness level has been reached, the iterations terminate and the algorithm outputs the final generation as the optimal solution.

To start the GA operation, arrays of k learner/subtask pairs are randomly generated, where k is the number of learners. In each array, the integrities of tasks should be checked. If there is any overflowing subtask within, that array will not be adopted as the initial solution. Taking these initial solutions as individuals (chromosomes), we need to encode them into populations (genomes) for creating the first generation. An example process of genome encoding is shown as Figure 2.

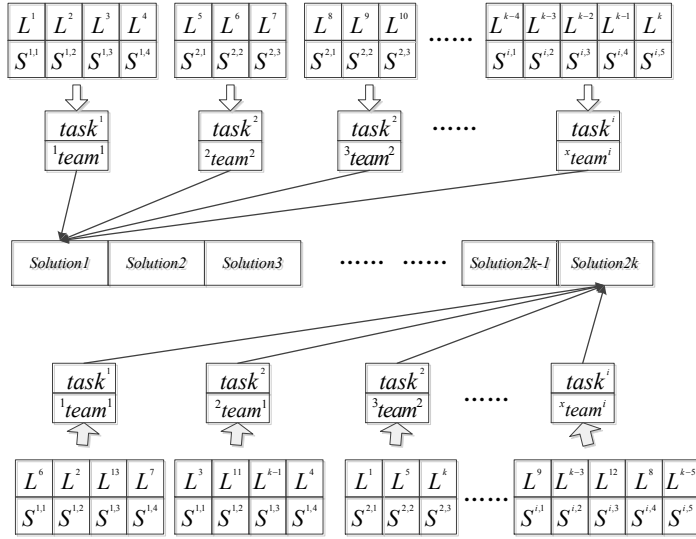


Figure 2. An Example Process of Genome Encoding

A fitness function transfers the task allocation from multi-objective optimization to single-objective optimization. For the first scenario mentioned in Section III, to make the proximate xCT , $^xDeP^i$ and $^xDeK^i$ between teams, total teams' variances of these parameters should be respectively minimized. However, for each attribute, several solutions may have different means but with the similar variances. A special situation is that the original difference of potential teams is little. To avoid the evaluation blindly terminates in a partial balance, we take minimizing the means of the DeP and the DeK of all teams into consideration. So we use the next equation as the fitness function:

$$R_m = \alpha \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{^xCT^i}{N^i} - \overline{CT} \right)^2} + \beta \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{^xDeP^i}{N^i} - \overline{DeP} \right)^2} + \gamma \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{^xDeK^i}{N^i} - \overline{DeK} \right)^2} + \varepsilon \overline{DeP} + \eta \overline{DeK} \quad (5)$$

For the second scenario, in a candidate solution, minimizing the total DeP and DeK is more important than minimizing the variance of CT . so we take the next fitness function:

$$R_m = \alpha \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{^xCT^i}{N^i} - \overline{CT} \right)^2} + \sum_{i=1}^n (\beta^x DeP^i + \gamma^x DeK^i) \quad (6)$$

where each Greek letter in (5) and (6) represents the weight for that attribute.

The aim of selection operator is to remove the poor solution with higher fitness. Then the selected individuals evolve to the next generation through the effect of crossover operator and mutation operation. We choose the top percent selection as the selection operator, the partially matched crossover as the crossover operator and the uniform mutation as the mutation operator. In particular, it should be noticed that the partially matched crossover has the function to deal with the appearance of the unfeasible solution that, after crossover, in a genome, a learner is repetitively assigned while another learner is leaved out. The work principles of the partially matched crossover and uniform mutation are shown as Figure 3 and Figure 4, respectively.

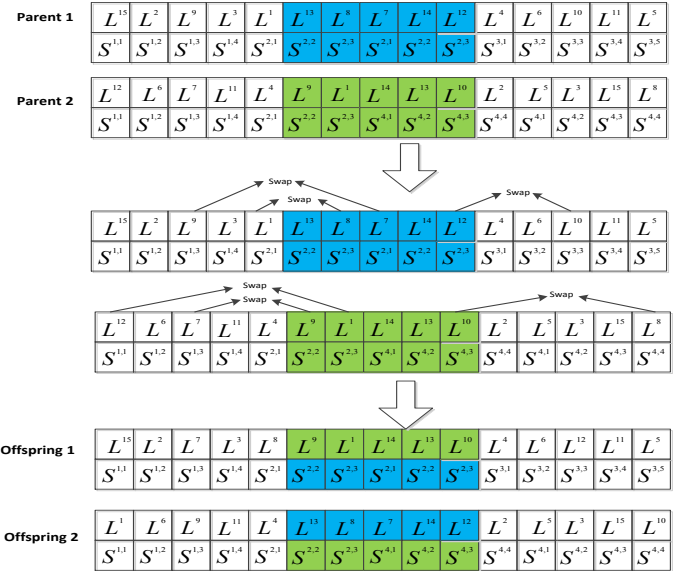


Figure 3. Work Principle of Partially Matched Crossover

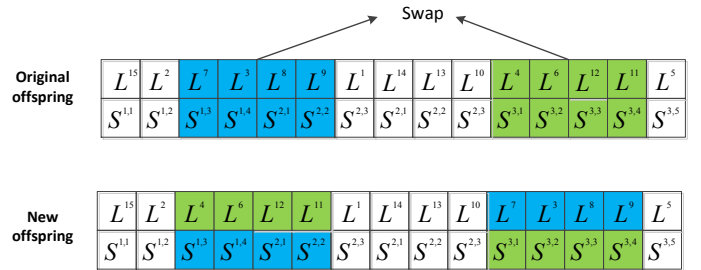


Figure 4. Work Principle of Uniform Mutation

Let the population size is $2k$. The pseudo code of GA is shown below:

The pseudo code of GA

Input: $KLS^k, CT^k, ST^{ij}, P_k^{ij}, N^i$

Output: $Team^x/Task^i$ pairs (sets of $L^k/S^{k,i}$ pairs)

begin: Calculate DeP , DeK , CT .

Randomly generate arrays of $k L^k/S^{ij}$ pairs

Check the task integrity in each array, give up unmatched ones.

Take the matched individuals as the initial population. Make the population size as $2k$.

for each individual \in population **do**

Evaluate the fitness of each individual using R_m .

end for

while iteration times $<$ max iteration time **do**

Select the individuals with lower fitness.

Use crossover operator to produce offspring.

Operate offspring through mutation operator.

Evaluate the fitness of new individuals using R_m .

Take the lower-fitness individuals to replace the old ones.

end while

Output the task allocation.

end

V. EXPERIMENT AND SYSTEM IMPLEMENTATION

A. Evaluation of Genetic Algorithm

In order to show the performance of the genetic algorithm method for the task allocation inference, we have coded the algorithm in the MATLAB tool. The data of learner information is randomly simulated by MATLAB, obeying normal distribution. For the experiment, we set the crossover possibility of genetic algorithm is 0.9, the mutation possibility of which is 0.2, and the terminal condition is iteration for 500 times. The population of learners is chosen to 100 persons and the number of subtasks is 200. In the first scenario, we set the weights $\alpha=0.5$, $\beta=0.15$, $\gamma=0.25$, $\varepsilon=0.05$, $\eta=0.05$. In the second scenario, we set the weights $\alpha=0.2$, $\beta=0.4$, $\eta=0.4$.

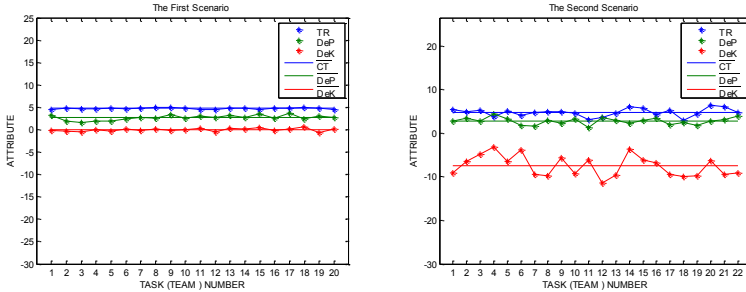


Figure 5. Task Allocation for Two Scenarios by GA

Having met the terminal condition, the algorithm outputs a solution, including 100 learner/subtask pairs, for allocating learners to their most appropriate subtasks. From Figure 5, in the first scenario, we can find that learners are divided into 20 teams and the values of total CT , DeP and DeK of each team are separately balanced on nearly same levels. That is to say, the three attributes between teams are all in close proximities, which mean that the teams have almost equal capabilities and preferences to achieve goals of their responsible tasks. And in

the second scenario, as the solution groups learners into 22 teams, the DeK attributes of each team are below 0, so that each team is competent to their allocated task. The result that the DeP level of each team is less than 3, because the team size is 3 to 6 persons, means the allocated tasks are enjoying high preferences as being deemed better than “interesting”.

B. User Interfaces

We employ MOODLE, a well known open source LMS, as our test LMS, by composing the TaaS and MOODLE to execute a simple type of teamwork-enhanced learning flow for mobile cloud based learning. The working principle is that mobile learners access learning resources and do their common learning activities through MOODLE, furthermore, they utilize functions supported by TaaS to facilitate collaborative learning.

We have launched a Linux instance, which contains one or a cluster of computers, of the Amazon Elastic Cloud Computing (EC2), running in Virginia, USA. We have configured the server environment as Apache + PHP + Mysql, and hosted our TaaS package on it. We have also uploaded the system package of MOODLE into the Amazon EC2, hosted on the same instance. The single-sign-on (SSO) technique is realized to enable users (teachers and learners) to log in to TaaS if they have valid MOODLE accounts. We have created a new database of TaaS for storing teamwork-related data, such as learners’ KLS capabilities, preferences, etc, meanwhile basic learning information, such as learner name, course name, etc, are invoked from MOODLE through its web service APIs, namely, `core_user` and `core_course`. After any change of team information, TaaS automatically updates it to MOODLE by invoking the `core_group` API.

The screenshots of UI are caught from a Samsung Tablet. Users are free to access TaaS and cloud-hosting LMSs by simple operation (e.g. finger actions on the touch screen) through their mobile devices, while the whole computing process is handled over the cloud. The UI of teachers’ main page of TaaS is shown as Figure 6. Teachers can click buttons to launch several events, such as starting each stage of the Jigsaw classroom and activating grouping by triggering the Inference Service. They also have authority to change the structure of surveys, pre-set the deduction for the learner’s each “unsatisfactory” outcome and so on.

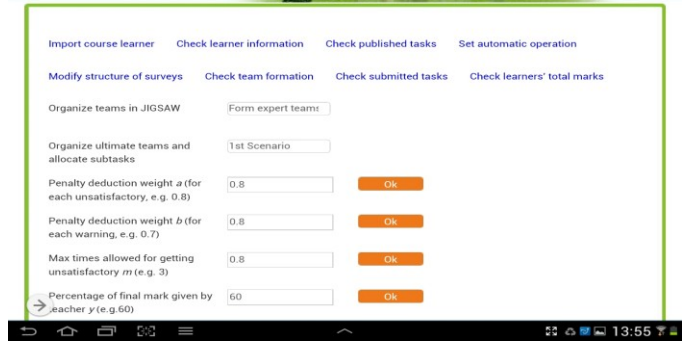


Figure 6. Main Page of the Teacher User

The UI of learners’ main page is shown as Figure 7. Learners’ capabilities in five areas are summarized in a bar

chart, and can be checked by their teammates. They can click buttons to participate in learning activities by entering new pages. The status of the message box changes when the new announcement arrives. Their team information and task information are shown on the bottom of the main page. While they are planning schedules using the Bulletin Service, the structure of tasks is scalable, by adding/reducing subtasks and adding/reducing the stages of subtasks.

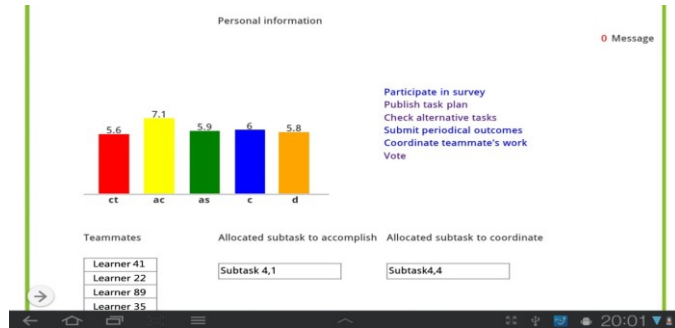


Figure 7. Main Page of the Learner User

VI. CONCLUSION

Mobile cloud-based learning is a new trend that promotes effects and conveniences of distance learning, but current researches lack sufficient efforts to facilitate collaborative learning in such new context. In this paper, we have followed the KTLE to orchestrate a mobile cloud-based learning flow, which consists of necessary steps to build a successful team. The execution of the new system is realized by running of several web services, each of which contributes functions by adding significant learning activities into original teamwork processes. Using these web services, learners are able to deepen their understandings of team learning purpose, practice their planning capabilities and supervise other team members for avoiding delays and keeping work efficiencies. Additionally, considering the limitation of less face-to-face communications in the mobile environment so that team membership and team roles are sometimes confused, we introduce a new approach for task allocation. This approach focuses on assigning learners highly-suited tasks, for the mediation that either balancing each team or booming each learner. As the attributes of candidate learners and tasks are complex, a genetic algorithm method is utilized to computationally determine the task allocation. Experiment results show that the method is competent to apply in real mobile cloud-based learning. We also have implemented these mobile-accessible web services over the Amazon EC2 cloud. Our further researches will focus on offering a client application for easier use through mobile devices, and bring in case studies to analyze learners' teamwork performance after they are assisted by the novel TaaS.

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